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14. ABSTRACT Several ocean color earth observation satellite sensors are presently collecting daily imagery, including the Hyperspectral Imager for the Coastal Ocean (HICO). HICO has been operating aboard the International Space Station since its installation on September 24, 2009. It provides high spatial resolution hyperspectral imagery optimized for the coastal ocean. Atmospheric correction, however, still remains a challenge for this sensor, particularly in optically complex coastal waters. In this paper, we assess the application of the cloud-shadow atmospheric correction approach on HICO data and validate the results with the in situ data. We also use multiple sets of cloud, shadow, and sunlit pixels to correct a single image multiple times and intercompare the results to assess variability in the retrieved reflectance spectra. Retrieved chlorophyll values from this intercomparison are similar and also agree well with the in situ chlorophyll measurements.					
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Assessing the Application of Cloud–Shadow Atmospheric Correction Algorithm on HICO

Ruhul Amin, David Lewis, Richard W. Gould, Weilin Hou, Adam Lawson, Michael Ondrusek, and Robert Arnone

Abstract—Several ocean color earth observation satellite sensors are presently collecting daily imagery, including the Hyperspectral Imager for the Coastal Ocean (HICO). HICO has been operating aboard the International Space Station since its installation on September 24, 2009. It provides high spatial resolution hyperspectral imagery optimized for the coastal ocean. Atmospheric correction, however, still remains a challenge for this sensor, particularly in optically complex coastal waters. In this paper, we assess the application of the cloud–shadow atmospheric correction approach on HICO data and validate the results with the *in situ* data. We also use multiple sets of cloud, shadow, and sunlit pixels to correct a single image multiple times and intercompare the results to assess variability in the retrieved reflectance spectra. Retrieved chlorophyll values from this intercomparison are similar and also agree well with the *in situ* chlorophyll measurements.

Index Terms—Atmospheric correction, cloud–shadow, hyperspectral imagery, ocean color, remote sensing.

I. INTRODUCTION

ACCURATE estimation of chlorophyll is very important for many reasons, including primary production models, carbon budgets, hypoxia, and eutrophication. Remote sensing has opened an effective way to estimate phytoplankton biomass and terrestrial products. Due to the tradeoff between spatial resolution, image coverage, and frequency in data acquisition, the coarse spatial resolution (1 km) optical sensors, such as the Moderate Resolution Imaging Spectroradiometer, are useful at continental- and global-scale biomass mappings [1]. However, to quantify biomass at local to regional scales, finer spatial resolution data are required, such as that provided by the Hyperspectral Imager for the Coastal Ocean (HICO).

The National Aeronautics and Space Administration's Earth Observing System and the European Space Agency programs provide ready-to-use remote-sensing products that are generated by science-based, calibrated, and validated algorithms [2], [3]. However, differences exist in these ready-to-use standard products due to sensor characteristics, product generation algo-

rithms, etc. Atmospheric correction is one of the biggest challenges for ocean color remote sensing, particularly in coastal waters. Different atmospheric correction methods on the same data can produce significantly different ocean color products such as water-leaving radiance (L_w) [4], [5].

The fundamental measurement in ocean color remote sensing is the water-leaving radiance, the upwelling spectral distribution of radiance from the ocean. Geophysical parameters such as chlorophyll can be retrieved from this water-leaving signal since it contains information about the optically active components in the water column. However, only about 10% of the total signal measured by the ocean color sensors contains information about the waters; the rest represents scattering from aerosols and air molecules [6]. The goal of the atmospheric correction over the ocean is to remove contributions from the atmosphere and reflection from the sea surface from the top-of-atmosphere (TOA) radiance recorded by the sensor, leaving L_w .

Gordon and Wang [7] developed an atmospheric correction scheme for the open ocean where the aerosol contribution is estimated using TOA radiance/reflectance signals obtained from near-infrared (NIR) bands. This approach assumes that the ocean is optically black in the NIR bands due to the strong water absorption. Although this technique works well in the open ocean, it breaks down in optically complex coastal waters since the black pixel approximation no longer holds true due to strong reflections from organic and inorganic particulate matters. If water-leaving radiance is not negligible in the NIR bands, then the retrieved aerosol loading will be overestimated, resulting in underestimated or even negative water-leaving radiances. The NIR-iterative procedure for the coastal waters [8] can reduce the number of pixels with negative retrievals in the coastal waters. More recently, another atmospheric correction approach for coastal water was proposed, which uses short-wave infrared (SWIR) bands [9]. This approach is based on the fact that ocean water absorbs strongly in this spectral region, and the contributions of the in-water constituents are negligible and can safely be considered dark. However, HICO does not have these SWIR channels. Furthermore, the atmospheric reflectance itself is significantly weaker in the SWIR region, requiring higher sensor signal-to-noise ratio (SNR). In such situations, the cloud–shadow atmospheric corrections [10], [11] can be very helpful, but this approach is limited to images that include at least one thick cloud and shadow pair. Thus, this approach cannot always be used for atmospheric correction. Since this approach depends on the assumption that atmosphere is nearly uniform throughout the image, it is more appropriate for sensors with high spatial resolutions such as HICO. If all of the conditions are right for an image, the cloud–shadow approach

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R. Amin, D. Lewis, R. W. Gould, W. Hou, A. Lawson, and R. Arnone are with the Naval Research Laboratory, Stennis Space Center, MS 39529 USA (e-mail: ruhul.amin@nrlssc.navy.mil).

M. Ondrusek is with NOAA/NESDIS/STAR, College Park, MD 20740 USA.

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can offer some advantages over the traditional approaches. For example, one of the major advantages of this approach is that the TOA radiances from the cloud, shadow, and sunlit pixels come from the same sensor, with all radiance components collected nearly simultaneously. As a result, the derived remote-sensing reflectance does not depend on the absolute radiance value since the sensor's response function (calibration factor) is canceled out [10]. This is very useful for sensors with high or unknown radiometric uncertainties. Currently, the cloud-shadow atmospheric correction is done by manually selecting pixels, which requires knowledge about TOA radiance. Also, the process can be somewhat time-consuming. Automating the scheme can be beneficial for ocean color remote sensing. Using the recently developed cloud-shadow detection technique over water [12], there have been some efforts to automate the approach [13]. However, automation still remains a challenge due to difficulties such as identifying thin clouds, cloud edge pixels, shadow edge pixels, homogeneous waters, etc.

In this paper, we apply the cloud-shadow atmospheric correction on HICO data and use *in situ* data to validate the results. We use *in situ* chlorophyll data from the literature and remote-sensing reflectance from coincident Aerosol Robotic Network-Ocean Color (AERONET-OC) sites and Hyperpro measurements to compare with HICO cloud-shadow atmospherically corrected data. We also use multiple sets of cloud, shadow, and sunlit pixels to correct the same image multiple times and intercompare the results.

II. MATERIALS AND METHOD

HICO is the first hyperspectral imager specifically made for environmental characterization of the coastal ocean from space. It has been operating aboard the International Space Station (ISS) since its installation on September 24, 2009 [14], [15]. HICO provides hyperspectral images at 100-m resolution optimized for the coastal ocean. It collects radiance at 128 contiguous spectral channels from 350- to 1070-nm range. However, it is most sensitive in the spectral wavelengths ranging from 400 to 900 nm, which are the most utilized spectral region for ocean color studies. Due to altitude and inclination of its orbit, HICO is limited to cover about 80% of the Earth's surface. However, this covered surface includes all tropical and most temperate coastal regions. Due to scene selection and data transfer issues, the sensor acquisition is limited in practice to one scene per orbit. HICO has SNR greater than 200, which enables retrieval of environmentally relevant quantities. The HICO data flow from the ISS provides a maximum of 15 scenes per day, and the sensor is managed by the U.S. Naval Research Laboratory (NRL).

We acquired a HICO scene with cloud-shadow over the productive waters of the Azov Sea, Russia, on July 13, 2010. The *in situ* chlorophyll values for this scene were taken from [16], where the values were determined analytically from water samples collected during the summer of 2010 in Taganrog Bay and the Azov Sea. We also acquired HICO scenes with cloud-shadow over Venice, Italy, on August 30, 2011, and over northern Gulf of Mexico on March 13, 2012, for which *in situ* AERONET-OC data were also acquired from the Acqua Alta Oceanographic Tower (AAOT) and the Wave-Current-Surge

Information System sites, respectively. An additional HICO scene with cloud-shadow was acquired over Chesapeake Bay on October 20, 2009, for which *in situ* Hyperpro data were acquired as well.

III. CLOUD-SHADOW ATMOSPHERIC CORRECTION

The cloud-shadow atmospheric correction method [10], [11] is appropriate for high-spatial resolution sensors such as HICO. This approach uses cloud and shadow pixels along with nearby sunlit pixels with similar optical properties. First, $L_a(\lambda)$, which represents the radiance from the atmosphere and sea surface, is estimated from a pair of adjacent pixels that are in and out of a cloud-shadow while ignoring the slight ($< 5\%$) differences in the remote-sensing reflectances ($R_{rs}(\lambda)$) under the two regions [17]–[20]

$$L_a(\lambda) = L_t^{\text{sun}}(\lambda) - \frac{L_t^{\text{sun}}(\lambda) - L_t^{\text{sdw}}(\lambda)}{1 - E_d^{\text{sky}}(\lambda)/E_d(\lambda)} \quad (1)$$

where $L_t^{\text{sun}}(\lambda)$ represents radiance from the sunlit pixel and $L_t^{\text{sdw}}(\lambda)$ represents radiance from the shadow pixel. $E_d^{\text{sky}}(\lambda)/E_d(\lambda)$ is the ratio between the downwelling sky irradiance to total downwelling irradiance which can be estimated using a radiative transfer model such as Radtran [21] for a given location and time. The value of $E_d^{\text{sky}}(\lambda)/E_d(\lambda)$ depends on atmospheric conditions such as visibility, ozone depth, etc. However, since $E_d^{\text{sky}}(\lambda)/E_d(\lambda)$ is applied on the difference between total radiance measured over the sunlit pixel ($L_t^{\text{sun}}(\lambda)$) and total radiance measured over the shadow pixel ($L_t^{\text{sdw}}(\lambda)$) and since this difference is significantly smaller than $L_t^{\text{sun}}(\lambda)$, errors in $E_d^{\text{sky}}(\lambda)/E_d(\lambda)$ have only very limited effects on $L_a(\lambda)$ estimation [10]. Since the errors in $E_d^{\text{sky}}(\lambda)/E_d(\lambda)$ estimation have negligible effects [10], $E_d^{\text{sky}}(\lambda)/E_d(\lambda)$ was calculated for this study with the default atmospheric parameters in Radtran [21]. According to [10], once $L_a(\lambda)$ is known, the remote-sensing reflectance ($R_{rs}(\lambda)$) at any pixel can be calculated from

$$R_{rs}(\lambda) = \rho \frac{L_t(\lambda) - L_a(\lambda)}{L_t^{\text{clid}}(\lambda) - L_a(\lambda)} \quad (2)$$

where $L_t^{\text{clid}}(\lambda)$ is the total radiance over the cloud pixel and ρ is the remote-sensing reflectance of the observed cloud. The value of ρ was determined according to [10] from a clear water pixel by assuming $R_{rs}(550 \text{ nm}) = 0.002 \text{ sr}^{-1}$ [22].

Remote-sensing applications such as the cloud-shadow scheme that are developed using dark and bright targets suffer from adjacency effects. Adjacency effect reduces the apparent surface contrast by decreasing radiance over bright pixels and increasing the brightness of the dark pixels. Edge pixels of the bright and dark targets are usually contaminated by the adjacency effects. These contaminated pixels could make it very challenging to quantify the accuracy of the atmospherically corrected data. To minimize errors due to adjacency effects, we selected pixels from around the center of the cloud and shadow regions by careful visual inspection of the spectra. Sunlit pixels were also carefully selected to ensure they were far enough from the shadow and cloud regions to minimize adjacency effects.

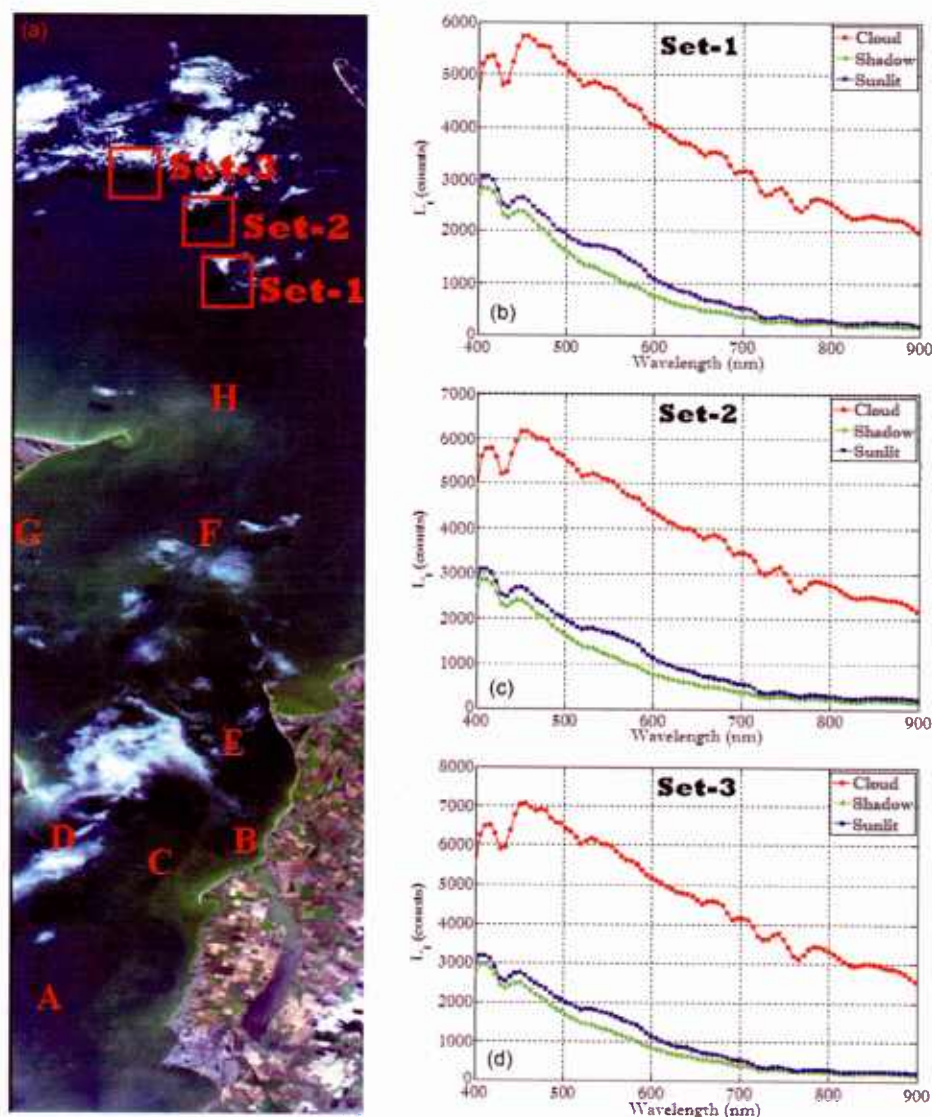


Fig. 1. HICO imagery from July 13, 2010, acquired over the Sea of Azov. (a) True color image overlaid with *in situ* point measurement locations (A–H) and cloud, shadow, and sunlit pixels used for correction of the atmospheric effects. The TOA radiances in raw counts from multiple sets of cloud, shadow, and sunlit pixels. (b) Set-1. (c) Set-2. (d) Set-3.

IV. RESULTS AND DISCUSSION

The cloud–shadow atmospheric correction was performed on the HICO image [Fig. 1(a)] from July 13, 2010, over the Azov Sea. TOA radiances (in raw counts) from multiple sets of cloud, shadow, and sunlit pixels were taken from the regions labeled with set-1, set-2, and set-3 in Fig. 1(a). The radiance spectra from set-1, set-2, and set-3 are shown in Fig. 1(b)–(d), respectively, where the cloud spectra are shown in red, the shadow spectra are shown in green, and the sunlit spectra are in blue. Using these three sets of radiances, we corrected the Sea of Azov scene for the atmosphere, which resulted in three sets of $R_{rs}(\lambda)$. We also took an average of these $R_{rs}(\lambda)$ and generated a fourth set of $R_{rs}(\lambda)$. Fig. 2 compares the four sets of results at eight *in situ* locations [A–H in Fig. 1(a)]. The blue, green, and red spectra are retrieved using set-1, set-2, and set-3, respectively, while the cyan is the average of the three sets. These reflectance spectra appear as typically expected reflectance spectra from chlorophyll-rich

waters. For example, the red spectral region is very important for remote sensing of coastal waters due to several spectral features unique to phytoplankton chlorophyll-a (absorption, scattering, and fluorescence) that takes place in this region. In the reflectance spectra of chlorophyll-rich water bodies, a distinct peak is observed somewhere in the wavelength range of 690–720 nm as can be seen in Fig. 2. This is mainly due to the relative minimum in total absorption (chlorophyll and water absorption), while the fluorescence term has small but measurable effects. The increase in the peak height is accompanied by a shift in the position toward the longer wavelengths with increasing chlorophyll, while the peak of the phytoplankton fluorescence has a permanent position at 685 nm. The effect of the chlorophyll fluorescence in eutrophic turbid waters is to fill the 670-nm reflectance trough and to augment the shorter wavelength shoulder of the 690–720 nm reflectance peak. For low chlorophyll concentrations, the region near 685 nm is considered the most appropriate feature of gaining information

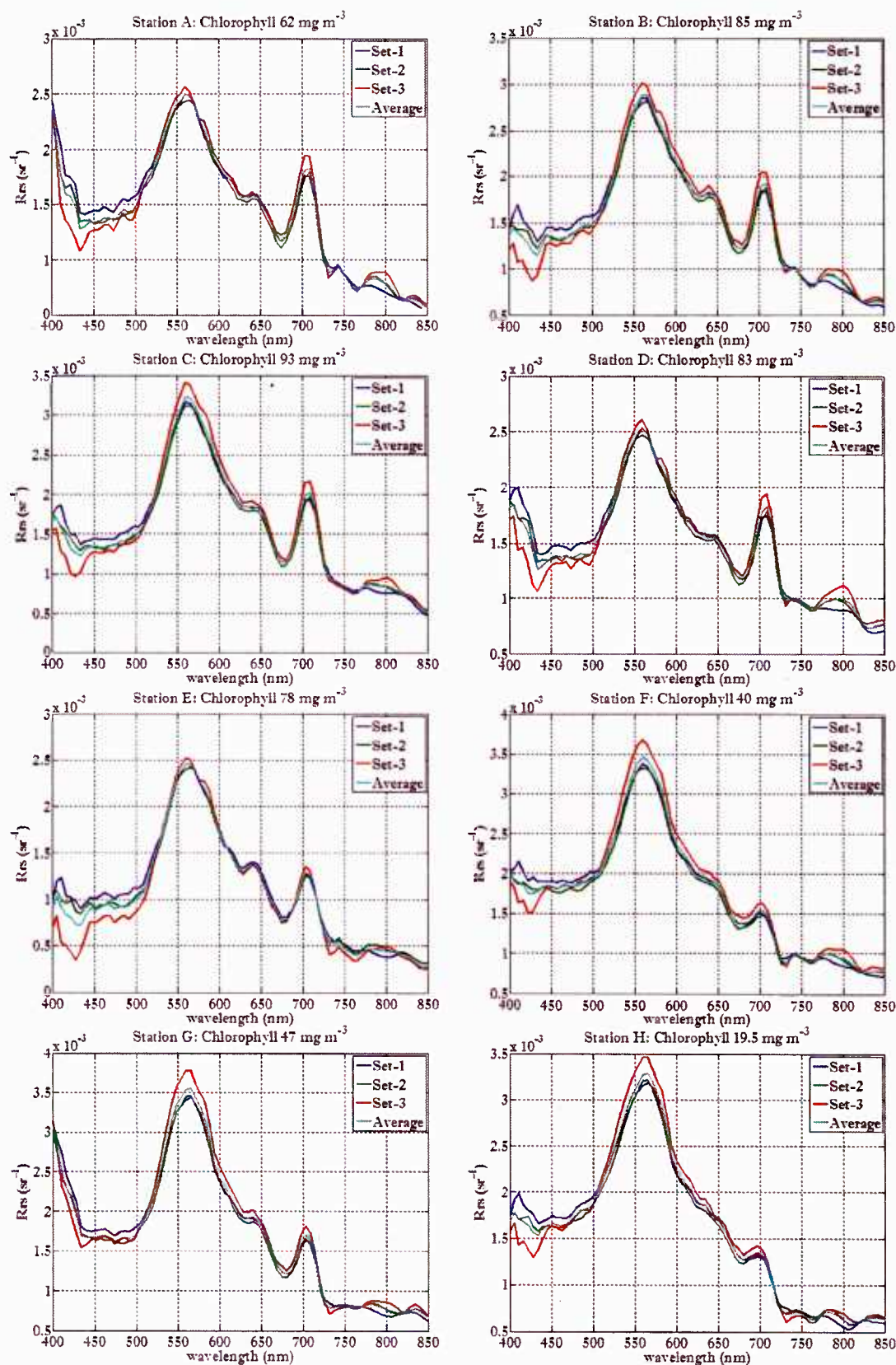


Fig. 2. Retrieved remote-sensing reflectance from HICO using multiple sets of cloud, shadow, and sunlit pixels. Letters A–H at the top of each subfigure indicate station name along with *in situ* chlorophyll concentrations.

on chlorophyll due to natural fluorescence signal [23]. However, for high chlorophyll concentration, the red-NIR peak can provide information about the concentration [24]. The example shown here has very high concentration of chlorophyll, where the minimum, maximum, median, and mean chlorophyll concentrations of the *in situ* stations were 19.67, 93.14, 63.86, and 70.6 mg/m³, respectively [16]. Due to these high chlorophyll concentrations, a pronounced red-NIR peak is expected in the reflectance which can be seen clearly in Fig. 2. Furthermore, an increase in the peak height and shift of the peak position toward longer wavelength is also expected with increasing chlorophyll [23]. This can be seen in Fig. 2, where the spectra with the lowest chlorophyll concentration (station H) have the smallest red-NIR peak while the spectra with the highest chlorophyll concentration (station C) have the largest peak. The slight shift of the peak position is also noticeable in Fig. 2, where the lowest chlorophyll spectra (station H) has peak around 697 nm while the highest chlorophyll spectra (station C) has peak around 709 nm. This demonstrates that the cloud-shadow atmospheric correction preserves the red-NIR peak characteristic, indicating that the shapes of the reflectance spectra are preserved with this approach. The shift of the peak position also demonstrates the value of the hyperspectral measurements that provides fine-resolution remote-sensing reflectance due to various optically active constituents in the waters. Excellent agreement in spectral shape can be seen in Fig. 2. However, there are slight differences in the spectral magnitudes. This is probably due to the residual contributions from the sky and the sea surface. In [10], it was suggested to remove a spectrally constant value from the calculated remote-sensing reflectance to obtain an average of zero for the spectral range 810–840 nm, where contributions from water are considered null [25]. However, in coastal waters, the NIR contribution may not be zero, and most importantly, the HICO results are very noisy in this region. Because of the noise, forcing the NIR reflectance to zero changes the spectral reflectance values considerably pixel to pixel, hence resulting in noisy retrieved products. Thus, we did not do any residual correction for this study. However, making accurate residual correction may improve the matchups.

The three-band reflectance model originally developed for estimating pigment contents in terrestrial vegetation [24] can also be used for chlorophyll estimation in the turbid waters [26]. For the July 13, 2010, Azov Sea scene, Gitelson *et al.* [16] determined the optimal HICO bands for the three-band model which are located at wavelengths of 684, 700, and 720 nm. The three-band red-NIR chlorophyll retrieval algorithm for HICO is expressed as $3_band = [R_{rs}(684)^{-1} - R_{rs}(700)^{-1}] \times R_{rs}(720)$, and it was found to agree well with the *in situ* chlorophyll [16]. This previous study [16], however, used the hyperspectral atmospheric correction algorithm (ATREM) [27], where estimation of aerosol contribution from TOA measurement using NIR bands could be an issue. Atmospheric corrections that use NIR band to estimate aerosol contributions often fail in the optically complex turbid waters because of higher turbidities which result in increased elastic reflectance and significant radiance contributions in NIR bands. Since HICO does not have SWIR channels and black pixel assumption does not hold true in turbid waters, aerosol estimation over turbid waters

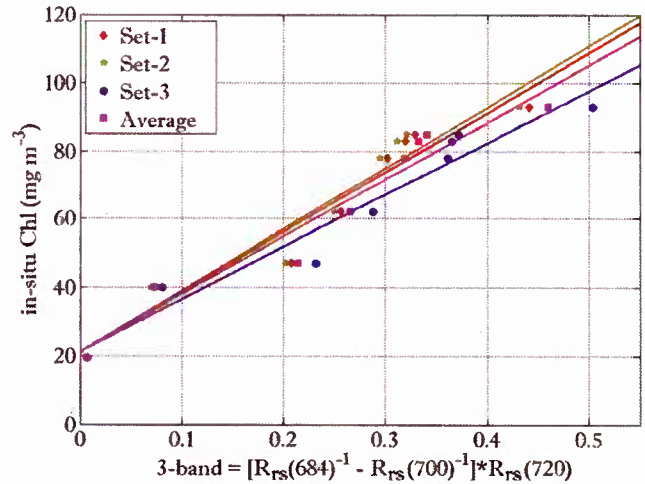


Fig. 3. *In situ* chlorophyll versus HICO-retrieved chlorophyll using the three-band model from multiple sets of $R_{rs}(\lambda)$.

is very challenging. Inaccurate aerosol estimation can lead to significant errors in retrieved ocean color products. However, the cloud-shadow atmospheric correction approach does not require any knowledge about aerosol contribution and can overcome some of these issues faced by NIR approaches.

To evaluate the performance of the four set results shown in Fig. 2, we compared the retrieved chlorophyll from the three-band reflectance model at the eight *in situ* locations with the *in situ* chlorophyll concentrations. The results are shown in Fig. 3. Very strong correlations can be seen between the retrieved and *in situ* chlorophyll values, where $r^2 = 0.94$ approximately for all four sets of results. Since the spectral magnitude is slightly different, the coefficients shown in Table I fluctuate slightly. The relationships developed from different sets of $R_{rs}(\lambda)$ and *in situ* chlorophyll are shown in Table I. These relationships were applied to all four sets of $R_{rs}(\lambda)$ to retrieve chlorophyll, and their performances were evaluated. Table I summarizes the results, where the root-mean-square error (rmse) is defined as $RMSE = \sqrt{\sum_{i=1}^N (Chl_{in\ situ}(i) - Chl_{HICO}(i))^2 / N}$ and the mean absolute percentage difference (APD in percent) is defined as $APD = 100(1/N) \sum_{i=1}^N (|Chl_{in\ situ}(i) - Chl_{HICO}(i)| / Chl_{in\ situ}(i))$, where $Chl_{in\ situ}(i)$ and $Chl_{HICO}(i)$ are *in situ* chlorophyll and HICO-derived chlorophyll values of the i th matchup, respectively, and N is the total number of matchup pairs. For all four estimated HICO chlorophyll products, the rmse values ranged from 5.79 to 10.10 mg/m³, while the APD values ranged from 9.91% to 14.32%, showing a good retrieval. However, the data set that we are using is very small, with a chlorophyll range higher than typical coastal waters. Thus, to get more robust uncertainty values, a larger data set with a more diverse chlorophyll range is necessary.

We also compared HICO cloud-shadow atmospherically corrected data with the *in situ* AERONET-OC data from the Venice AAOT and northern Gulf of Mexico WaveCIS sites on August 30, 2011, and March 13, 2012, respectively. For the AAOT site, the HICO image was acquired at 13:44 GMT, while the *in situ* AERONET-OC measurement was made at 13:45 GMT. For the WaveCIS site, the HICO image was acquired at 20:54 GMT, while the *in situ* AERONET-OC measurement was

TABLE 1
CHLOROPHYLL MATCHUP STATISTICS FOR THE FOUR SETS OF $R_{rs}(\lambda)$ RETRIEVED USING THE CLOUD-SHADOW APPROACH

Relationship derived from Set-1: $\text{Chl} = 175.61 \times (3_band) + 20.88$; $r^2 = 0.9374$		
Set	RMSE	APD
1	6.0515	10.4405 %
2	6.2148	10.3796 %
3	9.0141	12.7440 %
Average	6.2852	10.2145%
Relationship derived from Set-2: $\text{Chl} = 179.11 \times (3_band) + 21.17$; $r^2 = 0.9366$		
Set	RMSE	APD
1	6.1761	10.5912 %
2	6.0958	10.5290 %
3	10.0970	14.3240 %
Average	6.7944	10.5027%
Relationship derived from Set-3: $\text{Chl} = 152.99 \times (3_band) + 21.15$; $r^2 = 0.9428$		
Set	RMSE	APD
1	8.5335	12.2586 %
2	9.3290	13.0185 %
3	5.7873	9.9112 %
Average	7.3340	10.7536%
Relationship derived from Average: $\text{Chl} = 168.15 \times (3_band) + 21.05$; $r^2 = 0.9393$		
Set	RMSE	APD
1	6.3472	10.4985%
2	6.8226	10.4401%
3	7.4564	11.0774%
Average	5.9584	10.2821%

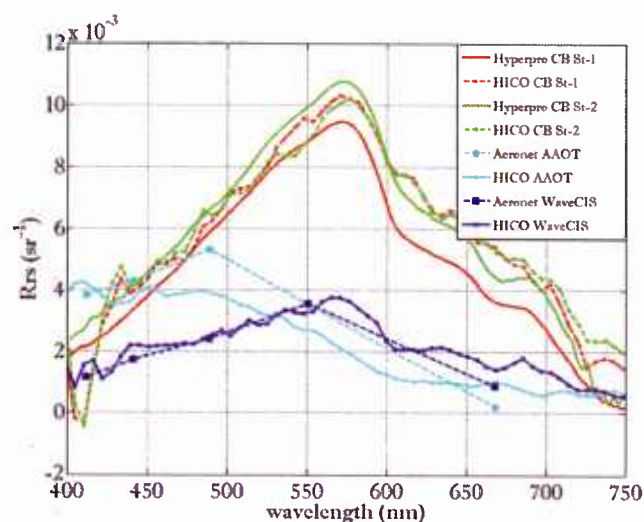


Fig. 4. Comparison of cloud-shadow-retrieved HICO $R_{rs}(\lambda)$ versus Hyperpro and AERONET-OC $R_{rs}(\lambda)$.

made at 16:27 GMT. Fig. 4 compares remote-sensing reflectance spectra derived from HICO to those from *in situ* measurements. The spectra represented by the red and green solid lines were collected using Hyperpro from the Chesapeake Bay on October 20, 2009, while the cyan spectra (dashed line with

solid circle) and blue spectra (dashed line with solid squares) were acquired from AAOT and WaveCIS sites, respectively. Reasonable agreement, in both spectral shapes and magnitudes, between HICO and *in situ* reflectances are obtained for these locations. As mentioned before, the residual contributions from the sky and the sea surface were not removed due to nonnegligible water contribution in the NIR region from the coastal waters. However, making accurate residual correction could improve the matchups particularly between Hyperpro and HICO spectra.

Even though the cloud-shadow atmospheric correction provides reasonably well results, it is a very limited approach. It requires a thick cloud pixel and a nearby thick shadow pixel where optical properties of the water in the shadow and neighboring sunlit pixels must be nearly identical. If the cloud, shadow, and sunlit pixels are not selected properly, the results could be spurious. Since this approach uses bright and dark targets, contaminated pixels from adjacency effect also need to be avoided. Appropriate cloud, shadow, and sunlit pixel selection is extremely important for the success of this approach. However, to our knowledge, there is no standard procedure to select these pixels from the TOA raw radiance counts. Thus, we carefully visually inspected true color images using ENVI image enhancement tools and selected appropriate pixels for each scene.

V. CONCLUSION

In this paper, we have investigated the applicability of cloud-shadow atmospheric correction on HICO data. Our analyses showed that ocean color products such as remote-sensing reflectance and chlorophyll retrieved from HICO imagery using cloud-shadow atmospheric correction method agree well with *in situ* data. However, it is a very limited approach for which success depends on the selection of the appropriate cloud, shadow, and sunlit pixels. Studies are necessary to come up with standards that qualify certain pixels as usable pixels that can be used to correct for the atmosphere.

REFERENCES

- [1] D. Lu, "The potential and challenge of remote sensing-based biomass estimation," *Int. J. Remote Sens.*, vol. 27, no. 7, pp. 1297–1328, 2006.
- [2] Y. Yamaguchi, A. B. Kahle, H. Tsu, T. Kawakami, and M. Pniel, "Overview of Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER)," *IEEE Trans. Geosci. Remote Sensing*, vol. 36, no. 4, pp. 1062–1071, Jul. 1998.
- [3] C. O. Justice, J. R. G. Townshend, E. F. Vermote, E. Masuoka, R. E. Wolfe, N. Saleous, D. P. Roy, and J. T. Morisette, "An overview of MODIS land data processing and product status," *Remote Sens. Environ.*, vol. 83, no. 1/2, pp. 3–15, Nov. 2002.
- [4] R. Amin, J. Zhou, A. Gilerson, B. Gross, F. Moshary, and S. Ahmed, "Novel optical techniques for detecting and classifying toxic dinoflagellate *Karenia brevis* blooms using satellite imagery," *Opt. Exp.*, vol. 17, no. 11, pp. 9126–9144, May 2009.
- [5] R. Amin, A. Gilerson, J. Zhou, B. Gross, F. Moshary, and S. Ahmed, "Impacts of atmospheric corrections on algal bloom detection techniques," presented at the 89th AMS Annu. Meet., Phoenix, AZ, USA, Jan. 11–15, 2008.
- [6] H. R. Gordon, T. Du, and T. Zhang, "Remote sensing of ocean color and aerosol properties: Resolving the issue of aerosol absorption," *Appl. Opt.*, vol. 36, no. 33, pp. 8670–8684, Nov. 1997.
- [7] H. R. Gordon and M. Wang, "Retrieval of water-leaving radiance and aerosol optical thickness over the oceans with SeaWiFS: A preliminary algorithm," *Appl. Opt.*, vol. 33, no. 3, pp. 443–452, Jan. 1994.
- [8] R. P. Stumpf, R. A. Arnone, R. W. Gould, P. M. Martinovich, and V. Ransibrahmanakul, *A partially coupled ocean-atmosphere model for retrieval of water-leaving radiance from SeaWiFS in coastal waters*, vol. 22, *SeaWiFS Postlaunch Technical Report Series*, S. B. Hooker and E. R. Firestone, Eds. Greenbelt, MD, USA: NASA, 2003, NASA/TM-2003-206892.
- [9] M. Wang and W. Shi, "Estimation of ocean contribution at MODIS near infrared wavelengths along the East Coast of the U.S.: Two case studies," *Geophys. Res. Lett.*, vol. 32, no. 13, p. L13 606, Jul. 2005.
- [10] Z. P. Lee, B. Casey, R. Arnone, A. Weidemann, R. Parsons, M. J. Montes, B. Gao, W. Goode, C. O. Davis, and J. Dye, "Water and bottom properties of a coastal environment derived from Hyperion data measured from the EO-1 spacecraft platform," *J. Appl. Remote Sens.*, vol. 1, no. 1, p. 011502, Dec. 2007.
- [11] P. Reinertsmann, K. L. Carder, and F. R. Chen, "Satellite-sensor calibration verification with the cloud-shadow method," *Appl. Opt.*, vol. 37, no. 24, pp. 5541–5549, Aug. 1998.
- [12] R. Amin, R. Gould, W. Hou, Z. Lee, and R. Arnone, "Optical algorithm for cloud shadow detection over water," *IEEE Trans. Geosci. Remote Sens.*, vol. 51, no. 2, pp. 732–741, Feb. 2013.
- [13] R. Amin, R. Gould, W. Hou, Z. Lee, and R. Arnone, "Automated detection and removal of cloud shadows on HICO images," in *Proc. SPIE*, 2011, vol. 8030, p. 803004.
- [14] M. D. Lewis, R. W. Gould, R. A. Arnone, P. E. Lyon, P. M. Martinovich, R. Vaughan, A. Lawson, T. Scardino, W. Hou, W. Snyder, R. Lucke, M. Carson, M. Montes, and C. Davis, "The Hyperspectral Imager for the Coastal Ocean (HICO): Sensor and data processing overview," presented at the IEEE Oceans, Biloxi, MS, USA, Oct. 26–29, 2009, pp. 1–9.
- [15] R. L. Lucke, M. Corson, N. R. McGlothlin, S. D. Butcher, D. L. Wood, D. R. Korwan, R. R. Li, W. A. Snyder, C. O. Davis, and D. T. Chen, "The Hyperspectral Imager for the Coastal Ocean (HICO): Instrument description and first images," *Appl. Opt.*, vol. 50, no. 11, pp. 1501–1516, Apr. 2011.
- [16] A. A. Gitelson, B.-C. Gao, R.-R. Li, S. Berdnikov, and V. Saprygin, "Estimation of chlorophyll-a concentration in productive turbid waters using a Hyperspectral Imager for the Coastal Ocean—The Azov Sea case study," *Environ. Res. Lett.*, vol. 6, no. 2, p. 024023, Apr.–Jun. 2011.
- [17] Z. P. Lee, K. L. Carder, C. D. Mobley, R. G. Steward, and J. S. Patch, "Hyperspectral remote sensing for shallow waters. 1. A semianalytical model," *Appl. Opt.*, vol. 37, no. 27, pp. 6329–6338, Sep. 1998.
- [18] J. T. O. Kirk, "Volume scattering function, average cosines, and the underwater light field," *Limnol. Oceanogr.*, vol. 36, no. 3, pp. 455–467, 1991.
- [19] A. Morel and B. Gentili, "Diffuse reflectance of oceanic waters (2): Bidirectional aspects," *Appl. Opt.*, vol. 32, no. 33, pp. 6864–6879, Nov. 1993.
- [20] Z. P. Lee, K. L. Carder, and K. P. Du, "Effects of molecular and particle scattering on model parameters for remote-sensing reflectance," *Appl. Opt.*, vol. 43, no. 25, pp. 4957–4964, Sep. 2004.
- [21] W. W. Gregg and K. L. Carder, "A simple spectral solar irradiance model for cloudless maritime atmospheres," *Limnol., Oceanogr.*, vol. 35, no. 8, pp. 1657–1675, 1990.
- [22] H. R. Gordon and D. K. Clark, "Clear water radiances for atmospheric correction of coastal zone color scanner imagery," *Appl. Opt.*, vol. 20, no. 24, pp. 4175–4180, Dec. 1981.
- [23] A. A. Gitelson, "The peak near 700 nm on radiance spectra of algae and water: Relationships of its magnitude and position with chlorophyll concentration," *Int. J. Remote Sens.*, vol. 13, no. 17, pp. 3367–3373, 1992.
- [24] A. A. Gitelson, U. Gritz, and M. N. Merzlyak, "Relationships between leaf chlorophyll content and spectral reflectance and algorithms for non-destructive chlorophyll assessment in higher plant leaves," *J. Plant Physiol.*, vol. 160, no. 3, pp. 271–282, Mar. 2003.
- [25] J. J. Mueller, C. Davis, R. Arnone, R. Frouin, K. L. Carder, Z. P. Lee, R. G. Steward, S. Hooker, C. D. Mobley, and S. McLean, "Above-water radiance and remote sensing reflectance measurement and analysis protocols," in *Ocean Optics Protocols for Satellite Ocean Color Sensor Validation*, J. L. Muller and G. S. Fargion, Eds. Greenbelt, MD, USA: NASA, 2002, pp. 171–182, Revision 3, NASA/TM-2002-210004.
- [26] G. Dall'Olmo and A. A. Gitelson, "Effect of bio-optical parameter variability on the remote estimation of chlorophyll-a concentration in turbid productive waters: Experimental results," *Appl. Opt.*, vol. 44, no. 3, pp. 412–422, Jan. 2005.
- [27] B.-C. Gao and C. O. Davis, "Development of a line-by-line-based atmosphere removal algorithm for airborne and spaceborne imaging spectrometers," in *Proc. SPIE*, 1997, vol. 3118, pp. 132–141.



Ruhul Amin was born in Sylhet, Bangladesh. He received the B.E. degree in computer engineering and the M.E. degree in electrical engineering from The City College of New York, New York, NY, USA, in 2005 and 2008, respectively, and the M.Phil. and Ph.D. degrees in electrical engineering from The City University of New York, New York, NY, USA, in 2008 and 2009, respectively.

Since 2009, he has been a Research Scientist with the U.S. Naval Research Laboratory, Stennis Space Center, MS, USA. He has developed optical algorithms to detect and classify harmful algal blooms from space. His current research interests include optical algorithm development, atmospheric corrections, cloud-shadow, fluorescence, and harmful algal blooms.



David Lewis received the B.S. degree in computer science from the University of Oklahoma, Norman, OK, USA, in 1984 and the M.S. degree in computer science and the Ph.D. degree in scientific computing from the University of Southern Mississippi, Hattiesburg, MS, USA, in 1993 and 2000, respectively.

While in Norman, he was involved in radar projects at the NOAA National Severe Storms Laboratory, which included investigation of tornadoes, gust fronts, and ionization effects of lightning. He transitioned from meteorological studies to land-based agricultural and then coastal oceanography remote-sensing projects. He has over 35 years in remote-sensing activities and is currently with the U.S. Naval Research Laboratory, Stennis Space Center, MS, USA, where he is involved in data fusion, vicarious calibration, bathymetry mapping, and algorithm development projects.



Richard W. Gould received the Ph.D. degree in oceanography from Texas A&M University, College Station, TX, USA, in 1987.

He has 30 years of oceanographic experience, including 22 years in remote sensing, satellite algorithm development, and optical instrumentation and measurements. He has authored or coauthored over 45 journal articles and over 200 conference presentations. He has developed and validated new multispectral and hyperspectral coastal ocean color algorithms, and he has transitioned satellite products

to both the Navy and the National Aeronautics and Space Administration (NASA). He has been involved on numerous interdisciplinary oceanographic programs funded by the Naval Research Laboratory (NRL), EPA, NOAA, NASA, and NSF. He manages the Bio-Optical/Physical Processes and Remote Sensing Section, NRL, Stennis Space Center, MS, USA. His current research interests include satellite algorithm development, uncertainty analyses, optical water mass classification, coastal hypoxia, surface/subsurface linkages, and physical/biooptical coupling.



Weilin (Will) Hou received the Ph.D. degree from the College of Marine Science, University of South Florida, Tampa, FL, USA, in 1997.

He is an Oceanographer with the U.S. Naval Research Laboratory, Washington, DC, USA, and manages the Hydro Optics Sensors and Systems Section. His research interests include ocean optics, underwater imaging, optical turbulence, remote sensing including LIDAR, numerical simulation, data management, instrumentation, and platforms including unmanned aerial and underwater vehicles.

Dr. Hou helps SPIE in organizing the Ocean Sensing and Monitoring Conference as part of the SPIE Defense and Security Symposium. He is the Editor of *Proceedings of SPIE* Vols. 7317, 7678, 8030, and 8372.



Adam Lawson received the B.S. degree in computer science from the University of Southern Mississippi, Hattiesburg, MS, USA, in 2009 while working as a STEP student for the U.S. Naval Research Laboratory (NRL).

He is currently with the Bio-Optical/Physical Processes and Remote Sensing Section, NRL, Stennis Space Center, MS, USA, working on satellite data processing and satellite calibration techniques utilizing various *in situ* data products.



Michael Ondrusek received the M.S. degree in oceanography from Texas A&M University, College Station, TX, USA, in 1989.

He worked at the University of Hawaii, Department of Oceanography from 1991 to 1998. He has been an Oceanographer with the NOAA Center for Satellite Applications and Research, College Park, MD, USA, for the past 15 years. His current research is on ocean color remote sensing in the Satellite Oceanography and Climatology Division's Ocean Sensor Branch.

This includes ocean color satellite calibration, validation, and algorithm development. He is currently a member of the JPSS VIIRS Ocean Color Cal/Val Team and the STAR Ocean Color Team. His interest includes *in situ* biooptical measurements, coastal runoff monitoring, algal blooms, phytoplankton pigments, phytoplankton physiology, and land/sea interactions.



Robert Arnone received the B.S. degree in geology from Kent State University, Kent, OH, USA, in 1971 and the M.S. degree in geophysical science from the Georgia Institute of Technology, Atlanta, GA, USA, in 1974.

He leads the Ocean Processes branch of over 40 scientists/technicians and staff of physical, biological, and optical and remote-sensing ocean personnel specializing in coupled dynamic processes (biophysical modeling), meso- and fine-scale physical processes (marginal seas, waves dynamics, and coastal processes), remote sensing and ocean optics (naval EO systems, hyperspectral algorithms, and satellite applications), and marine molecular processes. He leads research in basic and exploratory research and applied oceanography for Navy and federal agencies of the National Oceanic and Atmospheric Administration (NOAA) and the National Aeronautics and Space Administration (NASA). He is currently leading the Ocean National calibration/validation efforts for the satellite ocean JPSS for NASA, NOAA, and the Navy. He is coordinating the Naval Research Laboratory hyperspectral satellite Hyperspectral Imager of the Coastal Ocean, which was successfully launched to the International Space Station (in August 2009). He serves on science teams for NASA, NOAA, EPA, and the Navy, developing future satellite systems and establishing policy for ocean and coastal research. He has been an Adjunct Faculty with the Marine Science Department, University of Southern Mississippi (USM), Hattiesburg, MS, USA, since 1989 and with the University of Southern Alabama, Mobile, AL, USA. He serves on graduate student committees with the USM and Rosenstiel School of Marine and Atmospheric Science, Miami, FL, USA. He has over 90 scientific publications and more than 250 presentations. His specific expertise is in coupling biological optical and physical processes using ocean color satellite and ocean models. He has developed biooptical algorithms from satellites, which are applied to ecological forecasting models.

Dr. Arnone was the recipient of the Navy Meritorious Civilian Service Award in 2008, U.S. Navy honors and patents in 1980, NASA honors for Shuttle Astronaut Training program, U.S. Navy Employee of the year in 1998, Navy Royalty Transition Award for Automated processing in 2002, NOARL paper award in 1992, and NRL's Alan Berman Award Division award for best paper in 1998, 2002, and 2008.